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CORRELATION BETWEEN THE FEED AND THE MECHANICAL VIBRATION MEASURED DURING THE TURNING PROCESS USING SELF-ORGANIZING NEURAL NETWORKS

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Abstract. *The quality control of the surface finish of a piece produced in the turning process may be monitored by using several vibration signals processing techniques measured during the machining. Usually, the mechanical vibration measured during the metal cutting process depends on the several parameters, such as, the feed, cutting speed, cutting deep, etc. In this work, it will be employed the self-organizing neural networks, or Kohonen maps in order to correlate the mechanical vibration with the feed of the cutting tool in the turning process. For the classification task, the vibration signals measured during the machining have been processed in the time-scale using the Continuous Wavelet Transform. Subsequently, these signals were used as the inputs of a self-organizing neural network in order to study the influence of the cutting tool feed on the mechanical vibration.*

Keywords: *classification, self-organizing neural networks, surface roughness, vibration signals*

1. INTRODUCTION

The surface roughness of pieces produced by the machining process depend on several parameters, such as, the cutting speed, feed, cutting tool wear, mechanical vibration, etc. Usually, in a production line, the surface finish quality is estimated by measuring the roughness of pieces made in the machining process. Although this procedure is highly reliable, the total time spent to measure the roughness of the pieces could become impractical during the product quality control process. In this context, several techniques based on the on-line monitoring of the product surface quality are being extensively researched in the literature (Sick, 2002; Santos et. al., 1998; Guimarães et. al., 2008; Guimarães et al., 2011). For example, by using the information of the vibration signals measured during the machining process, it is possible to estimate the wear level of the cutting tool and the roughness of the pieces produced in the turning, milling or drilling process (Braun, 1986; Santos, 1998; Sick, 2002; Devillez and Dudzinsk, 2005; Guimarães et al., 2011).

After the measuring of the mechanical vibration signal in the machining process, the data are processing by several techniques in order to extract the amplitude, frequency or phase parameters which could be correlated either with the piece surface roughness or the cutting tool wear. Traditional techniques of the stationary signal processing, such as, the spectral analysis, cepstral analysis and the analysis in the time domain have been largely used for this purpose (Braun, 1986; Santos et al., 1998, Guimarães et al., 2008). Most recently, non-stationary signal processing techniques, as for example, the Wavelet Transform (Kilundu et al., 2011) and the time-frequency distributions (Peng et al., 2012) have been also employed for the analysis of the mechanical vibration generated in the machining process. By using these techniques, it is possible to detect the transient vibration patterns of the signals in the time domain measured during the metal cutting process.

Indeed, most of vibration signal processing techniques are used as the inputs of the classification systems of cutting tool wear used in the machining process (Sick, 2002; Kilundu et. al., 2011). For the classification of the surface quality of pieces produced by the milling process, Santos et al., (1998) have applied the artificial neural networks in order to estimate the roughness of the product during the machining process. In this work, Santos et al. (1998) employed the spectral analysis and the low-pass filters to try to correlate the roughness of the pieces with the mechanical vibration measured in the process. Devillez and Dudzinsk (2005) used the fuzzy systems for the classification of the roughness of steel tubes in the turning process. They also used the Fourier Transform in order to extract the frequency and amplitude components of the signals due the mechanical vibration caused by the movements from the cutting tool.

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The relationship between the feed and surface roughness of pieces have machined by the turning process can be obtained by empirical equations available in the literature (Machado and da Silva, 2004). However, the roughness also depends on the mechanical vibration and several cutting parameters. Unfortunately, this relationship is highly nonlinear since the mechanical vibration of the tool, workpiece and machine tool set depends on the tool geometry, piece and tool material, natural frequency of mechanical system, etc. Hence, the objective of this work is to correlate the feed of the cutting tool with the mechanical vibration of steel shafts made by the turning process using the self-organizing artificial neural networks. First of all, the vibration signals measured during the metal cutting process were processed using the Continuous Wavelet Transform (CWT). It can be observed that when the tool feed increases, the transient vibration components generated by the cutting process also change. Subsequently, the vibration signals in the wavelet domain have been used as the inputs of the the self-organizing neural. It will be shown in the analysis results that the transient vibration components caused by the turning process could be correlated with the cutting tool feed.

2. MECHANICAL VIBRATION AND CUTTING PARAMETERS

In a general way, the lower is the cutting tool feed, the lower is the surface roughness of the piece produced by the turning process. However, it is difficult to establish a relationship between mechanical vibration, feed and piece surface finish analytically. Indeed, the mechanical vibration generated during the metal cutting process is highly nonlinear with several frequencies components (Sick, 2002) since the signals measured during the machining process depends on the cutting parameters, as for example, cutting speed, piece material, cutting tool feed, etc. Moreover, there are several noise sources that may contaminate the vibration response, such as the movements between the blank and machine tool, or the chatter vibration (Devillez and Dudzinsk, 2005), vibration of the mechanisms from machine tool, etc.

According to Santos et al. (2000), the larger is the cutting tool feed, the lower is the amplitude of the mechanical vibration produced in the turning process. Guimarães et al (2011) and Santos et al. (1998) have demonstrated that the turning process produces vibration amplitude modulation components caused by the contact between the cutting tool and the metal piece. The amplitude of these components and the modulation repetition pattern are associated with cutting speed of the turning process. In this work, the modulation amplitude of vibration components caused by the contact between the blank and the tool will be extracted using the Continuous Wavelet Transform (CWT). Moreover, the evolution of the feed and the analysis of the behavior of the transient vibration components produced by the machining will be studied by means of the self-organizing neural network.

3. TOOLS OF SIGNAL PRE-PROCESSING

3.1 Continuous Wavelet Transform

In the traditional spectral analysis, the vibration signal in the time domain is compared with harmonic functions. In this way, by using the Fourier Transform (TF), the frequency components of the vibration signals measured during the turning process can be obtained easily (Sick, 2002; Santos et al., 1998; Guimarães et al., 2011). Nevertheless, the features of the transient vibration signals caused by the turning of the shafts could not be easily extracted by the conventional spectral analysis. Since that the window in the time domain used in the FT has infinity duration, it is not possible to extract neither when the transient component has occurred and nor its duration in the time-frequency plane (Cohen, 1995). In this case, appropriate techniques of the non-stationary signal analysis should be used for this purpose.

In this work, it will be applied the Continuous Wavelet Transform (CWT) to the vibration signals measured during the shafts machining process. The CWT has several advantages when compared to the others time-frequency representations, as for example, the Wigner Distribution (WD), the Choi-Williams Distribution (CWD) and the Short Time Fourier Transform (STFT) (Peng, 2012). The WD has high resolution in the time-frequency plane but for multicomponent signals the cross-terms may be mask the analysis (Cohen, 1995). The CWD has a high computational cost and the STFT has constant time-frequency resolution which can difficult the extraction of the transient vibration components caused by the turning process. Therefore, the CWT to be used in this work, *CWT(t,a)*, is defined by:

$$CWT(t,a) = \frac{1}{\sqrt{|a|}} \int_{0}^{\infty} x(\tau)\psi^*(t-\tau)d\tau \tag{1}$$

where ψ is the mother wavelet which is compared with signal in the time domain, $x(t)$, a is a scale factor used in the dilation of $\psi(t)$ and τ is the delay time used in the convolution integral from CWT. In practice, there exist different types of mother wavelet that can be used in the correlation with $x(t)$. In this work, it will be used the Morlet Wavelet for the extraction of the features of transient vibration produced by the metal cutting. There are two reasons for the choice of this wavelet. Firstly, it was demonstrated that the vibration signals with amplitude modulation generated in the turning process are similar to this kind of wavelet (Guimarães et al., 2011). Moreover, the central frequency of the band of $\psi(t)$ can be easily associated with the scale factor used in its dilation.

ISSN 2176-5480

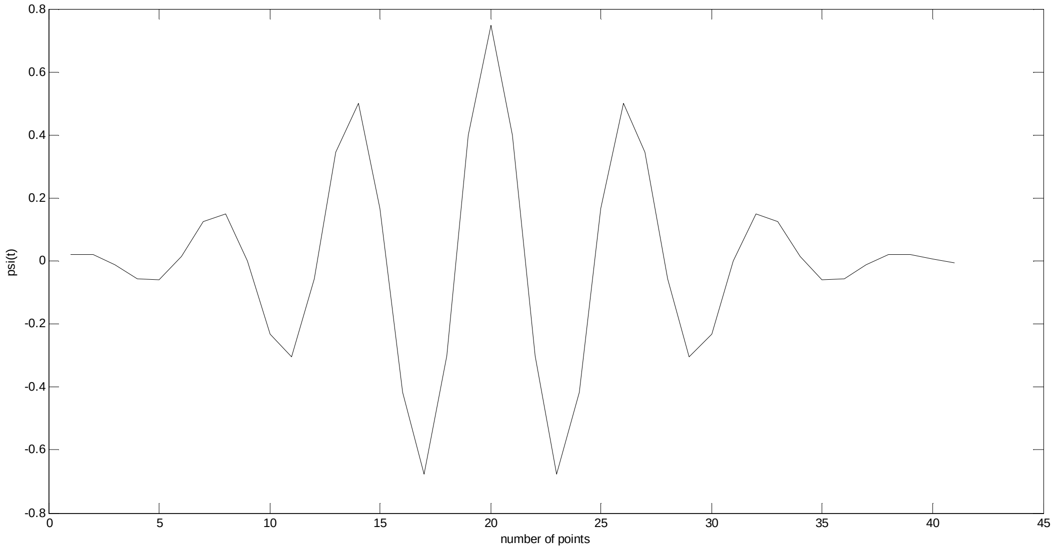

Figure 1. Morlet wavelet to be used in the analysis of the vibration signals measured in the turning process.

Figure 1 illustrates the Morlet wavelet used in the CWT of the vibration signals to be measured in the machining process. The relation between the scale and frequency, *f*, of Morlet wavelet family correlated with the vibration signals is described by Eq. (2) (Heneghan et al., 1994):

$$a = V \log_2 \left(\frac{k_\psi}{f} \right) \tag{2}$$

where the parameter *V* represents the scale division in octaves and the k_ψ a constant to be determined. In this work, this equation will be used in order to estimate the frequencies of the transient vibration components due to the shafts turning. By using Eq. (2), it can be seen that the larger is the scale factor, the lower is the frequency of the components of signal, that is, the larger is the dilation of the mother wavelet.

3.2 Calculation of the vibration signal amplitude in the wavelet domain

After the computation of the time-scale map provided by the CWT, it is necessary to compact the vibration data in the wavelets coefficient matrix. In this work, it will be determined for each scale (or frequency) the root means square of wavelets amplitude. Therefore, the time-scale matrix will be transformed into a vector with the vibration amplitude corresponding to the scales used in the decomposition of the signal. This data vector will be the inputs of the self-organizing neural network for the classification or separation of classes (clustering) of the vibration signals measured during the metal machining. The root mean squares of the vibration amplitude for each wavelet scale are given by (Heneghan et al., 1994):

$$x_{rms}(a) = \int_0^\infty CWT^2(t,a)\,dt \tag{3}$$

such that $x_{rms}(a)$ represents a measure of the signal energy density in each scale in the time domain. When the vibration signal is processing by the CWT, the envelope shape of the signal is obtained for each scale or frequency in the time-scale map. Equation (3) gives the mean value of the vibratory energy of the signal transient components in each scale. So, if the cutting tool feed increases during the experiments and if the vibration signal amplitude increases or decreases, the result of eq. (3) will indicate this effect.

ISSN 2176-5480

4. KOHONEN MAPS

An Artificial Neural Network may be defined as a computational model inspired in the nervous system from humans (Haykin, 1994). In the signal processing context, the Multi-layer Perceptron Neural Networks have been largely used in mechanical vibration problems, as for classification tasks, as for regression and modeling problems by using input and output data measured in the system (Worden et al., 2011). In a general way, for a Perceptron Neural Network (PNN), usually the input data are transmitted for the next neurons layer by means of the synapses and so on, until the last neurons layer which are transformed in the output data. Each neuron of the neural network is modeled by an activation function, or transfer function, and the most common models available in the literature are the sigmoidal function, the hyperbolic tangent function and the linear one (Haykin, 1994; Worden et al., 2011). On the other hand, in classification problems, the last neurons layer is modeled by the hyperbolic tangent or sigmoidal activation functions (output data is 0 or 1). In the other hand, in regression problems, the last neurons layer uses linear activation functions (continuous output data).

The objective of this work is to study the correlation or similarity between the feed of the cutting tool and the workpiece surface roughness by using only the vibration signal measured during the turning process. Since the PNN need of input and output data for the training process, this type of neural network could not be used for this problem. Hence, we choose the Self-Organizing Neural Networks (SONN), or Kohonen Maps, for this investigation.

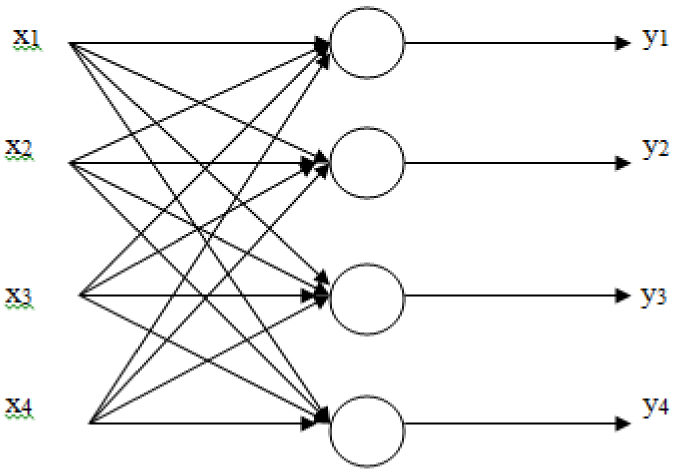

Figure 2. Topology of an Artificial Neural Network.

Figure 2 shows the topology of an Artificial Neural Networks with 4 inputs and 4 outputs. In the training process of a PNN, the weights of each neuron are fixed by the minimization of the error between the desired output and the computed output by the neural network. After the optimization, it is expected that the output from PNN is as close as possible of data used for the training or learning of the neural network. The idea and the concept of a SONN are different when compared to the PNN. In the processing of data in the SONN, there are several synapses by connecting the neurons of the same layer. Furthermore, the output data in the SONN are unknown and the correlated input data after the training are separated in classes (clustering). In the case of SONN, the vector of weights of each neuron, *w*, updated in the iteration index *i+1* is given by (Haykin, 1994):

$$w_{i+1} = w_i + \eta(x - w_i) \tag{4}$$

where the parameter η represents the learning rate and the variable x is the input matrix have defined by Eq. (5) provided to SONN for the training. The algorithm used for the training of SONN is called competitive learning because only the weight from winner neuron is adjusted in the current iteration. For the definition of the winner neuron in the competitive learning process, usually the distance (dist) between the inputs and the weights is computed for each neuron (Haykin, 1994):

$$dist_i = \sqrt{\sum_{j=1}^{n} (x - w)^2} \tag{5}$$

ISSN 2176-5480

where n is the quantity of samples of input data used in the training. Therefore, according to Eq. (5), the neuron which has the minor distance is the winner of the competition. In other words, if the distance between the input data and the weights is small, it means that the correlation between these parameters is high and vice-versa.

5. NUMERICAL AND EXPERIMENTAL PROCEDURE

The vibration signals to be processed by the SONN were measured during the turning process of shafts made of ABNT 1020 steel with hardeness 125 HB (Guimarães et al., 2011). For this analysis, 12 specimens with diameter of 17 mm were submitted to the machining process. In all experiments, the cutting depth of workpieces was 0.5 mm. The values of the feed to be considered in the experiments are shown in the Table 1. In the data sampling, it was considered only one value for the cutting speed: 400 rpm. Hence, the range of feed values considered in this work was of 0.047 mm/cycle to the 0.299 mm/cycle, as can be seen in Table 1.

Table 1. Values of the cutting speed and feed used in the experiments.

Cutting Speed	Feed (mm/cycle)					
400 rpm	0,047	0,104	0,166	0,187	0,250	0,299

For the clustering of the vibration signals, they were measured by using a 4214 model accelerometer from Bruel & Kjaer manufacturer has attached to the toolholder of the machine tool. Table 2 describes the parameters values used for measuring the vibration data in the time domain. It is not necessary to use a signal conditioning unit since this accelerometer has an integrated signal pre-amplifier for increasing the output signal gain. The signals measured during the turning process were directly connected to a data acquisition board from National Instruments manufacturer. Subsequently, the software Labview® was used to save the data file in a txt format.

Table 2. Parameters values used in the acquisition of vibration signals from turning process.

Sampling Frequency	Number of Points	Acquisition Time	Sensitivity of Accelerometer
2000Hz	4000	2.0 s	$1.05mV/m/s^2$

After the vibration data aquisition, the signals in the time domain were processed by using the CWT as defined in Eq. (1). Subsequently, the time-scale matrix provided by the CWT was transformed in a vector by using the rms value given by Eq. (3). Equations (1) and (2) were implemented to analyse the vibration signals via Matlab® 2009ª software. The next step of the clustering procedure was to train the Self-organizing Neural Network using the neural toolbox available in the Matlab® 2009a as well. In this procedure, the rms vectors provided by Eq.(3) for each feed considered in the experiments were transformed in a matrix to be used in the learning process from SONN. Finally, it was possible to correlate the feed with the vibration signal amplitude by using the output data provided by the SONN.

6. ANALYSIS OF THE RESULTS

Figure 3 shows the vibration signal in the time domain measured in the turning process by considering a cutting tool feed of 0.047 mm/cycle and rotation speed of piece equals to 400 rpm. For this case, the CWT shown in Fig. 4 illustrates two components of frequency in the scales of 13 (6.4 Hz) and 26 (1.41 Hz), respectively. It is interesting to note that the vibration amplitude in the scale of 13 is approximately constant with the time. On the other hand, the amplitude of frequency component in the scale of 26 is varying periodically with the time. From this analysis, it is believe that the vibration component in the scale of 13 can be caused by noise source due to the vibration of the machine tool. However, the vibration component with amplitude modulation in the scale of 26 should be produced by the metal cutting process during the shafts turning.

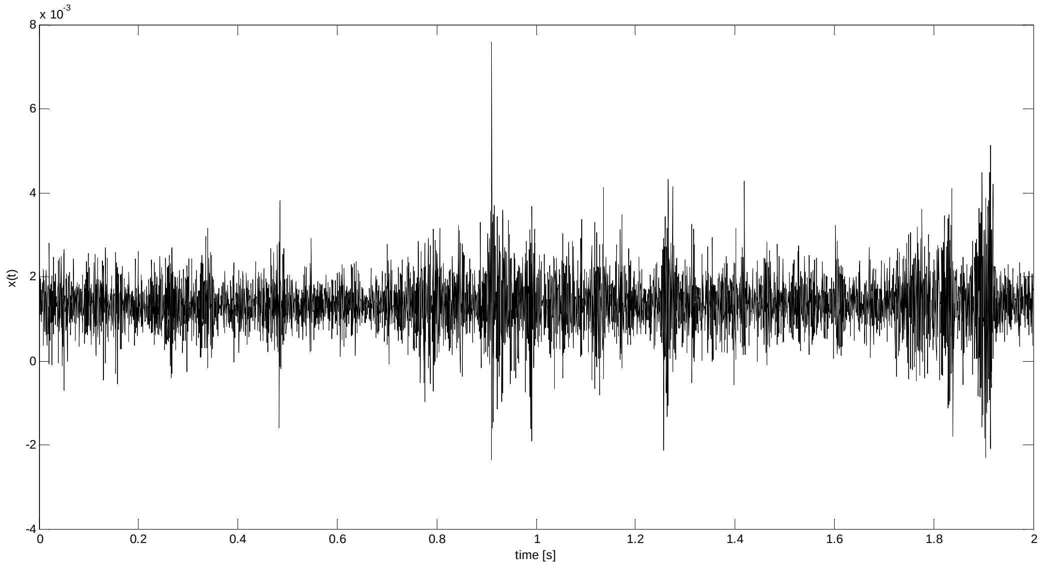

Figure 3. Vibration signal from turning process with feed of 0.047 mm/cycle and speed of 400 rpm.

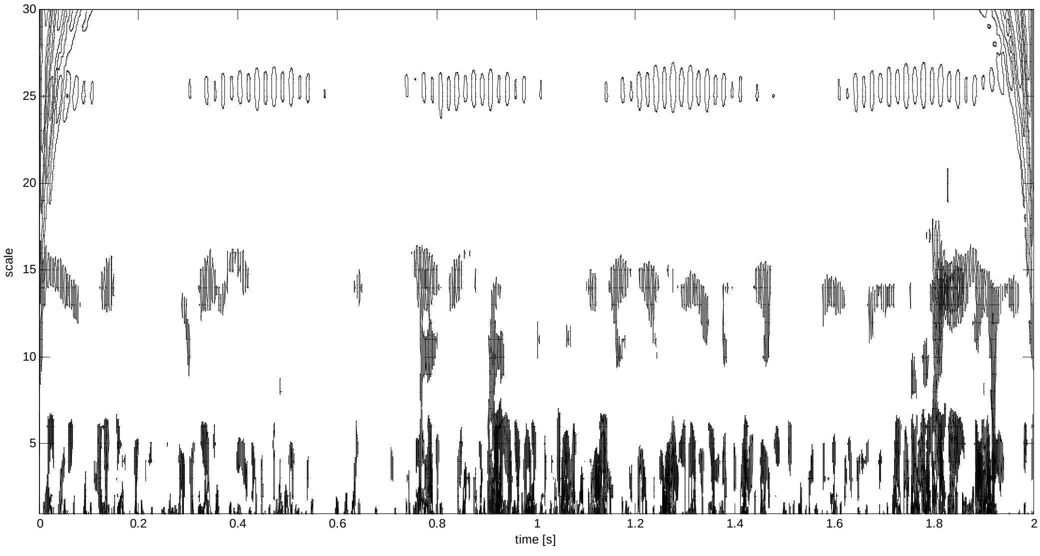

Figure 4. CWT of x(t) measured in the turning process with feed of 0.047 mm/cycle and speed of 400 rpm.

When the feed increases, it can be seen in the time-scale map from Fig. (5) some vibration components generated by the metal cutting process. For example, for the feed of 0.0104 mm/cycle and the rotation of 400 rpm, there are transient vibration components in the scales shown in Fig. (5). On the other hand, these transient signals could not be observed in the time-scale map for the vibration measured in the turning process with the feed of 0.047mm/cycle and cutting speed of 400 rpm. From this analysis, it was demonstrated that when the cutting tool feed changes, the material removal process generates transient vibration components in the signals measured during the machining. Furthermore, figures (4) and (5) display several vibration components with amplitude modulation due to the metal removal process produced by the movement from cutting tool. By using the CWT, it is possible to extract the localization and of scale of these transient vibration components have produced by the shafts turning process.

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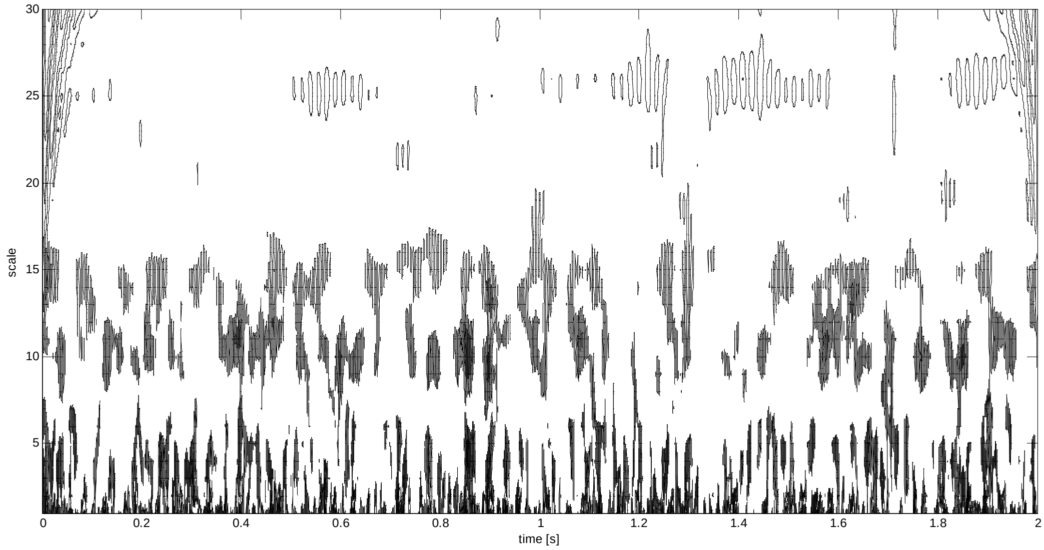

Figure 5. CWT of x(t) measured in the turning process with feed of 0.104 mm/cycle and speed of 400 rpm.

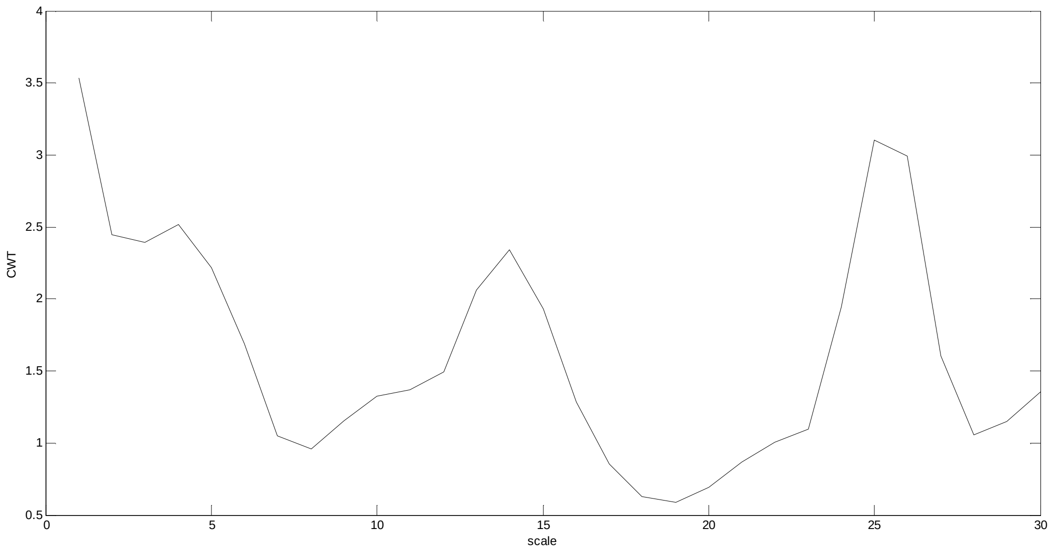

Figure 6. Amplitude of the transient vibration components in the scales from 0 to 30.

After the calculation of the CWT from vibration signals for the cutting parameters described in Table 2, the wavelet amplitude were compacted in a matrix using the Eq. (5). This matrix has 6 rows and 30 columns. The six rows are the inputs from Self-Organizing Neural Network and the columns are the samples to be considered in the training of SONN. For the competitive learning algorithm of the SONN, it was used a learning rate, η=0.001, which is default in the training of the SONN by using the software Matlab® R-2009a (Haykin, 1994). For the training of the SONN, the CWT matrix was normalized by its maximum value (Haykin, 1994).

For the cutting tool feed of 0.104 mm/cycle, the transient vibration components measured in the turning process have the behavior shown in Fig. (6). It can be seen in this figure that the maximum amplitude of the vibration produced by the turning process occurred in the scales of 1 to 3 (25.4 to 20.2 Hz), 13 to 15 (6.4 to 5.1 Hz) and 23 to 26 (2.0 to 1.4 Hz). It is interesting to note that competitive learning procedure clusters these amplitudes in the class labeled as 1 (one), according to Fig. (7). Thus, for the values of the feed range considered in this work, the maximum vibratory energy caused by the turning process is concentrated in the scales of 1 to 3, 13 to 15 and 25 to 26. Otherwise, the minor amplitude of vibration for all values of the feed belongs to the class labeled as 2 (two). In this class, there are the scales from 18 to 22 (3.6 to 2.2 Hz).

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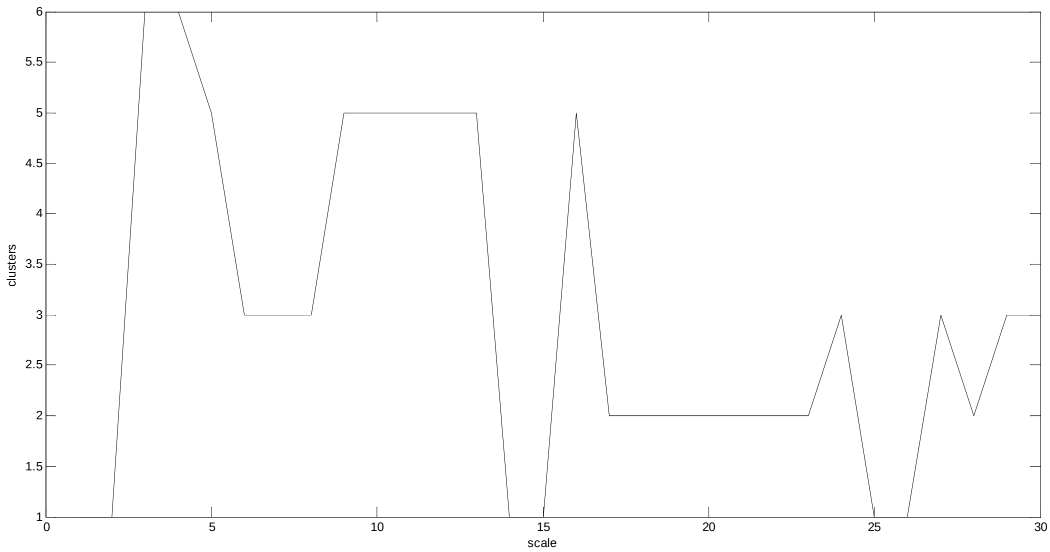

Figure 7. Clustering of the transient vibration data measured in the turning process.

7. CONCLUSIONS

In this work, it was applied the Continuous Wavelet Transform (CWT) for the characterization of the transient vibration signals produced by the shafts turning process. By using the CWT, it was possible to detect the vibration components with amplitude modulation in the time scale plane caused by the metal cutting process. This analysis procedure was applied to the vibration signals measured during the machining by changing the feed from cutting tool in the range of 0.047 to 0.299 mm/cycle. The objective was to verify if the feed has some influence in the mechanical vibration generated by the contact between the cutting tool and the workpiece.

Subsequently, the vibration data generated by the CWT were used in the configuration and training of a Self-Organizing Neural Networks (SONN). By using the SONN, the vibration amplitude for the several values of feed were clustered in classes. After the competitive learning process, the maximum values of the vibration amplitude did belong to one class and the minor vibration amplitude were concentrated in other class. Therefore, it was possible to identify the vibration frequencies caused by the cutting process that have minimum and maximum amplitude for the whole range of feed considered in this work. In the future, it will be studied the influence of the feed and mechanical vibration on the finish surface of the machined pieces.

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